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Thermal load prediction in district heating systems

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Abstract

Optimal operation of district heating (DH) systems usually relies on the forecast of thermal demand profiles of the connected buildings. Depending on the purpose of the analysis, thermal request can be required at various levels, from building level to thermal plant level. In the case of demand response for example, thermal request is necessary at a building level to evaluate its applicability and at a plant level to determine the effects. Thermal request profiles are quite different, depending on the observation point. Total requests are not just the summation of the downstream requests, mainly because of the thermal transients. The heat losses also contributes to modify the curves, although generally in a smaller way.
In this work, a multi-level thermal request prediction is proposed. This approach has the aim of evaluating the thermal request in the various sections of DH network with reduced computational resources. This includes a compact model for the prediction of building demand and a network model in order to compose together the requests at the various levels. The application to a portion of the Turin district heating network is proposed. This shows that the network dynamics significantly affects the evolution, especially at peak load.

Keywords: load forecast, multi-level approach, network model

1. Introduction

District heating (DH) is an increasingly widespread technology for house heating and domestic hot water production, especially in highly populated areas [1]. In some European countries as Denmark, this is used to provide more than 60 % of the heat demand to buildings [2]. DH is an important technology for improving energy efficiency in urban areas. In fact, it enables shifting heat generation from domestic boilers to a) high efficiency plants [3,4] b) industrial waste heat [5, 6] c) renewable energy sources [7, 8]. This represents a strength from two points of view: from an end-user perspective, because the energy cost is generally lower and because the issues related to the domestic boiler maintenance and control are avoided; from a community and environmental point of view, because it avoids environmental emissions thanks to the lower primary energy consumption and the decarbonisation of the energy source.
Management of DH networks is a crucial point to achieve high efficiency. A smart selection of the operating plants allows a significant primary energy saving (especially when RES and waste heat are available). Additional primary energy savings can be obtained through an optimal selection of working conditions of pumps [10]. Optimal management of networks in case of malfunctions (leakages or pump failure) can lead to a drastic improvement of the comfort conditions in buildings[11]. Proper use of storage can lead to a significant

decrease of primary energy consumption [12]. Optimal network management also allows solving possible hydraulic bottlenecks and connect as much buildings as possible to a network without modifying the network pipelines [13].

Intelligent management of DH systems relies on detailed knowledge of the thermal request at various levels:building level, distribution network level or thermal plant level. Some examples are:

- Thermal demand at building level for operating actions such as demand side management [14-16].
- Request at a distribution network or a group of distribution networks for storage installation (optimal design, position) and management [17], as well as for defining optimal pumping strategies.
- Thermal load at a plant level for taking decisions on optimal plant operation.

The thermal load profile at the plants might be very different than the demand at the buildings, because of the thermal transients, the losses towards the environment and the mixing effects of the various streams coming from the various areas of the network. Depending on the application, it is important to consider the thermal request at proper level.

The thermal request profile within the day at a building level, can be predicted through advanced tools for building analysis (such as Energy Plus) or black box models (neural networks, machine learning etc). The first approach [18, 19] uses physical principles to calculate thermal dynamics and energy behavior of buildings. Models based on this approach are expected to provide precise results because they simulate the physics of the phenomenon. On the other hand, they require high computational resources and precise input data in order to obtain results with a sufficient level of accuracy. This makes them unsuitable when a large number of buildings is considered.

In contrast, black box approaches provide results with low computational costs but results are less detailed [20, 21]. These models are suitable for applications to large systems and when dealing with measurements available in thermal substations. Various works in the literature propose models for predicting the overall request of DH relying on historical data [22-25].

A schematic including the models currently used for building demand evaluation is reported in Fig. 1 [26]. The figure shows that, when the demand of single buildings is evaluated, small time frames are considered, while in case of higher number of buildings the time frame is generally high, especially when the analysis is made for planning purpose. In case of DH management, the thermal demand of buildings is necessary with low time frame, of the order of few minutes.

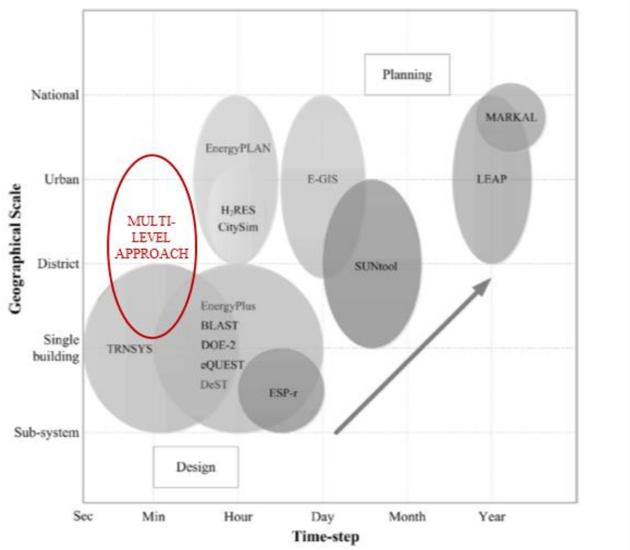

Fig. 1 Model for thermal request prediction in DHN [26]

In this framework, the present paper proposes a multi-level method to predict the request of buildings in DH systems. It is based on a compact model for the prediction of building demand profiles in DH. Prediction of the thermal demand is obtained by means of the data that are usually available in building connected to DH (e.g. measurements from smart meters used for billing purposes). This allows one evaluating the request of all buildings connected to a network with low computational costs and good accuracy.

In the multi-level prediction method a physical model of the DH network is combined with the building demand prediction.. This allows one to properly aggregate the request at various levels (at a subnetwork level, at a thermal plant level, etc.,) taking the transients, heat losses and mixing into account. The multi-level prediction approach can be applied to optimal DH management. In a multi-energy framework, it allows defining opportunities and constraints for the use of heat pumps [27-29], thermal energy storage units [30-32] or to apply a demand response management.

2. Methodology

2.1 Multi-level approach

In this paper, a multi-level approach is proposed to predict the thermal request at various network levels. The thermal load at the plants may be very different than the summation of the thermal demands of the buildings, due to the network dynamics, the heat losses and the different behaviour of the buildings in the various zones of the network. The methodology here presented consists in the following steps:

- A smart predictor of the thermal demand evolution of the buildings. This is a compact model which relies only on the data that are usually available for the thermal substations in modern networks, such as the inlet and outlet temperatures and the mass flow rate on the primary side.
- A network model able to combine together the demand of the various buildings and to account for the fluid flow and heat transfer in the network.

The two models are described in section 2.2 (Building demand prediction) and 2.3 (Network model).

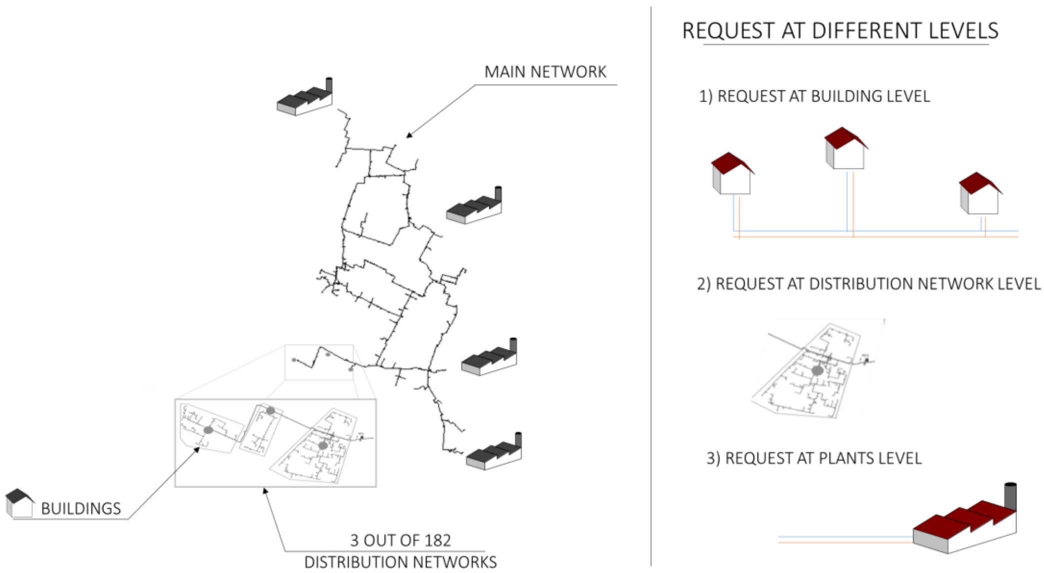

Fig. 2. Schematic of the different level requests

2.2 Buildings demand prediction

Building demand prediction is mainly based on the idea to simplify the thermal profile, so that it can be identified using a small number of variables. Using this approach, prediction of these variables is sufficient to construct the demand profile, instead of predicting the complete evolution. This allows reducing the effects of two types of errors: those due to model complexity and those due to data gathering and transmission. In fact, complex models require a large amount of data to be calibrated and are particularly sensitive to measurement errors; in addition, when dealing with collection of data from a large number of substations, missing data or wrong measurements to be filtered off might appear. When compact models are used, these issues can be easily detected and tackled.. Fig. 3 shows the main characteristics of the adopted approach. The various parts are described in the following subsections.

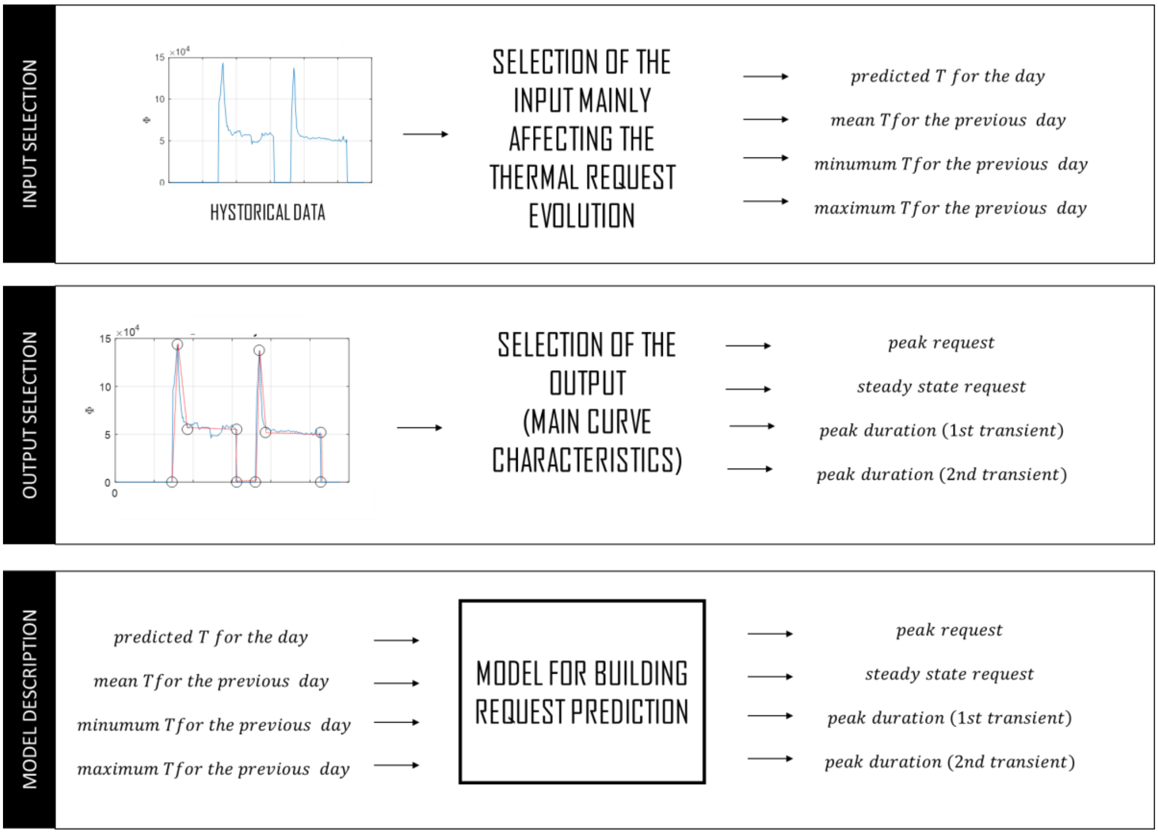

Fig. 3. Structure of the prediction model for building demand profiles

<u>2.2.1 Selection of the output of the prediction model</u>

Looking at the building request evolution shown in Fig. 3a, it is clear that the main features are: a peak demand occurring when the heating system is switched on and a steady state following the peak. The time when peaks occur and the duration of the steady state depend on the heating schedule, i.e. when the system is switched on and off. The following quantities can be thus evaluated for each building:

- the maximum elevation of the peak;
- the steady-state heat demand;
- the time which is needed for reaching the maximum point of the peak after the heating system is switched on;
- the time which is needed for reaching the end point of the peak after the maximum;

The schedules for the heating systems are set on the substations upon request of the end-users, therefore these are known values which do not need an estimation. All these quantities are reported in Fig. 4.

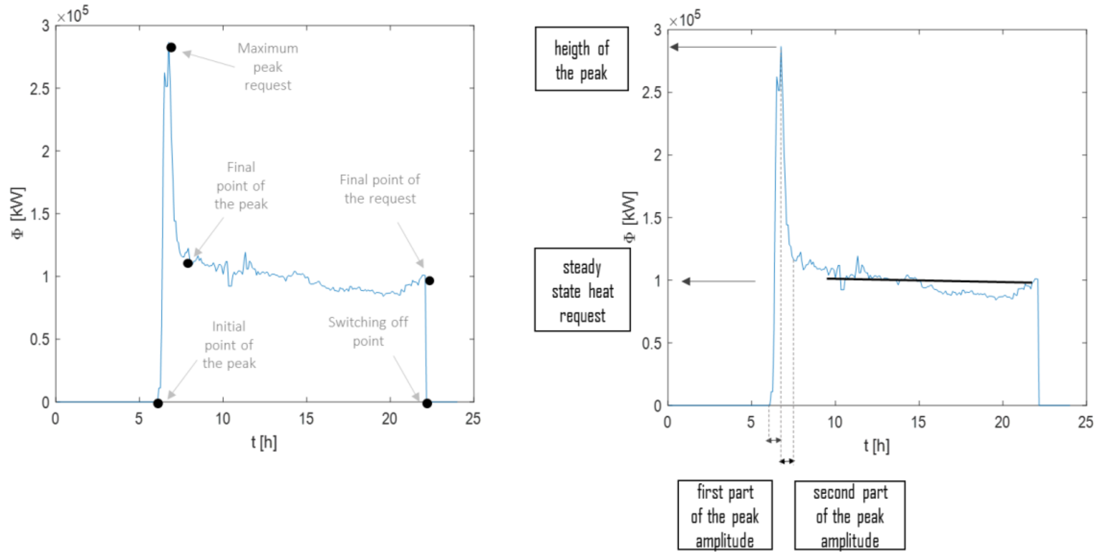

Fig. 4 Key points in the demand profiles

Detection of these quantities should be made automatic, because it is necessary to produce a sufficiently large historical dataset for a large number of buildings. For this reason, the following procedure has been implemented using a proper software (in this case a Matlab function has been created):

- first of all, abnormal values are eliminated by excluding the peaks which values are too large when compared with the corresponding steady states (e.g. more than 4-10 times, depending on the average external temperature) and the values which do not fit at all correlations with the external temperatures;
- the maximum elevation of the peak is evaluated as the highest value of each day;

$$\Phi_{\max} = \max(\Phi) \tag{1}$$

- the steady-state heat demand is evaluated as the average of all the thermal load values comprised between the end point of the peak and the following switching off time.

$$\Phi_{steady} = \frac{1}{N}\sum_{t=t3}^{t4} \Phi \tag{2}$$

  where N is the number of samples between t_3 (end peak time) and t_4 (switching off time).
- the time the system requires for reaching the maximum point of the peak from the switching on time is evaluated as the difference between the time the two events occur.

$$w1 = t2 - t1 \tag{3}$$

  t_1 is the switching on time and t_2 the maximum peak time.
- the time the system requires for reaching the end point of the peak from the maximum is evaluated as the difference between the time the two events occur.

$$w2 = t3 - t2 \tag{4}$$

  where t_3 is the end-peak time

The evaluation of the final point of the peak requires particular care. Each points after the maximum peak is gathered and it is considered as the end of the peak if one of the two following options is satisfied:

- the slope of the curve has an absolute value which is lower than a threshold;
- the heat flux is smaller than the steady state.

When a heating system which is switched on more than once a day is considered, the same approach is used as many times as the number of operation periods. Therefore, the daily evolution is divided into various periods (when the system is switched on i.e. the thermal power is different than zero) and for each period the same analysis is repeated.

2.2.2 Selection of the input of the prediction model

In order to identify the most appropriate input of the model, various parameters have been considered:

- the average temperature of the previous day, $T_{m,d-1}$;
- the minimum temperature of the previous day, $T_{min,d-1}$;
- the maximum temperature of the previous day, $T_{max,d-1}$;
- the average temperature of the current day, $T_{m,d}$;
- the solar radiation, I;
- the air humidity, ϕ;
- the wind velocity, v;

In order to evaluate which of these quantities mostly influence the main characteristics of the thermal demand evolution, a correlation analysis has been performed by using the Pearson index. The Person index of two variables is defined as the covariance over the product of their standard deviations. Results of the correlation analysis show that the quantities that mostly affect the thermal request evolutions are the four temperatures. The air humidity and wind velocity have a negligible effect on the demand profile. The latter is justified by the fact that Turin is located in a geographic area characterized by low wind velocities. Solar radiation mainly affects the evolution of indoor temperatures, while its main effect on the demand profiles is somehow captured by the difference between minimum and maximum temperatures. For these reasons only the four temperatures are considered as the input for the model.

2.2.3 Forecast model

A linear model has been used for the evaluation of the main curve characteristics. The schematic of the model used is presented in the last box in Fig. 2 The form of the linear model can be described by equation 5.

$$Y = \beta_0 + \beta_1 X \tag{5}$$

The vector Y (n x 1) includes the curve main characteristics, the vector X (m x 1) includes the set of independent variable evaluated through the correlation analysis, β0 is the constant term vector (n x 1) and β1 is the coefficient matrix (n x m).

2.3 Network model for changing the request level

A network model is used in order to analyse the water dynamics within the pipelines. with the model is based on a graph approach, which is used to provide a mathematical representation of the network structure [33]. Following a 1D approach, each pipe of the network is considered as a branch that starts from a node, (the inlet node) and ends in another node (the outlet node). The incidence matrix, **A**, describes the network topology by expressing the connections between nodes and branches. This matrix has as many rows as the number of nodes and as many columns as the number of branches. The general element A_{ij} is equal to 1 or -1 if the branch j enters or exits the node i and 0 otherwise. The thermal fluid-dynamic model considers:

- the mass conservation equation applied to all the nodes and the momentum conservation equation applied to all the branches. These equations are here considered in steady state, since fluid-dynamic perturbations travel the entire network in a period of time smaller than the time step adopted for calculations (60 s). The resolution of the fluid dynamic relies on an iterative approach because the problem is nonlinear since the two equation are coupled and the dependence of pressure from the mass flow is quadratic. Further details on the method are available in [34]. The solved equations are:

$$\mathbf{A} \cdot \mathbf{G} + \mathbf{G}_{\mathbf{ext}} = 0, \tag{1}$$

$$\boldsymbol{G} = \boldsymbol{Y} \cdot \boldsymbol{A}^T \cdot \boldsymbol{P} + \boldsymbol{Y} \cdot \Delta \boldsymbol{p}_{pumps}, \tag{2}$$

where **G** is the vector including the mass flow rates in branches, $\mathbf{G}_{\mathbf{ext}}$ the vector includes the mass flow rates exiting the nodes towards the extern, **P** the vector including the pressures in the nodes and $\Delta \mathbf{p}_{\mathbf{pumps}}$ is the pressure difference in the pumping stations. The diagonal matrix **Y** represents the fluid dynamic conductance of branches that can be written as:

$$Y = R^{-1} = \left[\frac{1}{2} \frac{G}{\rho S^2} \left(\frac{f}{D} L + \sum_k \beta_k \right) \right]^{-1} \tag{3}$$

- The thermal model is expressed in transient form since thermal perturbations travel the network at the water velocity, which is the order of few meters per second, depending on the request and the portion of network. Therefore temperature variations take a lot of time to reach the thermal plants.

$$\mathbf{M}\dot{\mathbf{T}} + \mathbf{KT} = \boldsymbol{\gamma} \tag{4}$$

where **M** is the mass matrix, **K** is the stiffness matrix, **T** is the vector of nodal temperatures and **γ** the vector of known terms.

3. Case Study

The test case considered in this work is the Turin DH system. The buildings connected to the network are about 6500 (each building includes a heat exchanger). The main transport network links the thermal plants to the various groups of consumers located on the same areas, while 182 distribution networks connect the transport network to the single buildings. For further details on the analysed system refers to [32].

The large number of buildings connected to the Turin network makes the use of automatic system for the evaluation of thermal profiles necessary. Forecast of the thermal profiles is done by means of data gathered at the substations. The measured quantities are:

- the mass flow rate at the primary side of the heat exchanger, G;
- the temperature at the inlet section of the primary side, T1;
- the temperature at the outlet section of the primary side, T2;
- the temperature at the inlet section of the secondary side, T4;
- the temperature at the outlet section of the secondary side, T3;
- the environmental temperature, Tenv.

Fig. 5 shows the evolution of data gathered in a distribution network of the Turin system; mass flow rates (G) and thermal power (ϕ) are shown. The latter quantity is calculated from the measurements of mass flow rate and the two temperatures on the primary side. Most of the heating systems are switched off during the night and switched on between 5 a.m. and 6 a.m. When a system is switched on, the mass flow rate and, consequently, the thermal profile present a peak, due to the low temperature of the fluid at the secondary side of the substation heat exchanger. The number of shutdowns of the systems is selected by the end-users and it is different in the various buildings (one, two or three times a day). This is a very important point for the thermal load prediction.

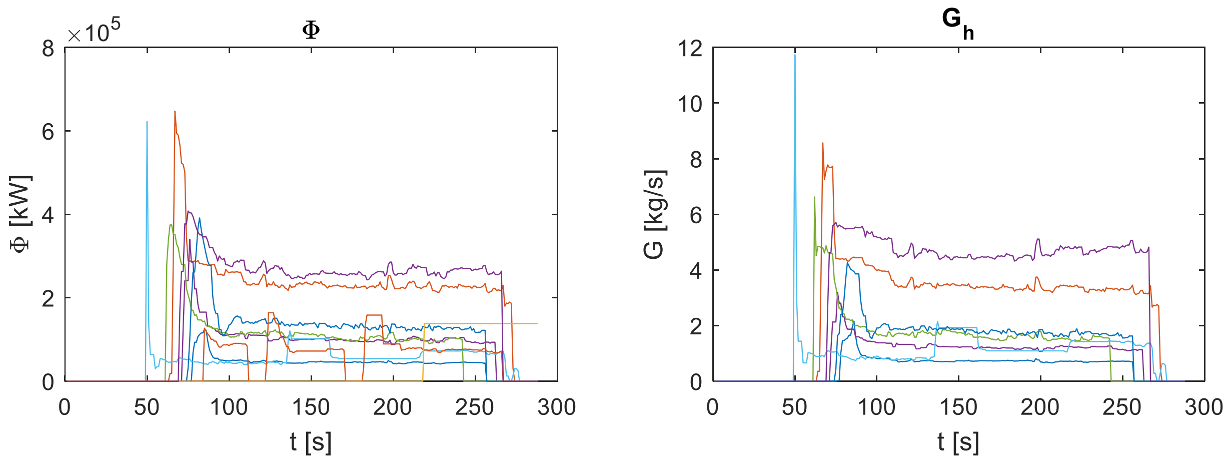

Fig. 5. Daily data gathered in the substations

4. Results

Results presented in this paper are divided in three main parts. The first part (section 4.1) concerns the evaluation of the thermal request at building level (orange arrows in Fig. 6). The second part (section 4.2) deals with the thermal request at distribution network level (red arrow in Fig. 6). In the third part (section 4.3) results related to the thermal request at the thermal plants (dark red arrow in the Fig. 6) are shown and discussed.

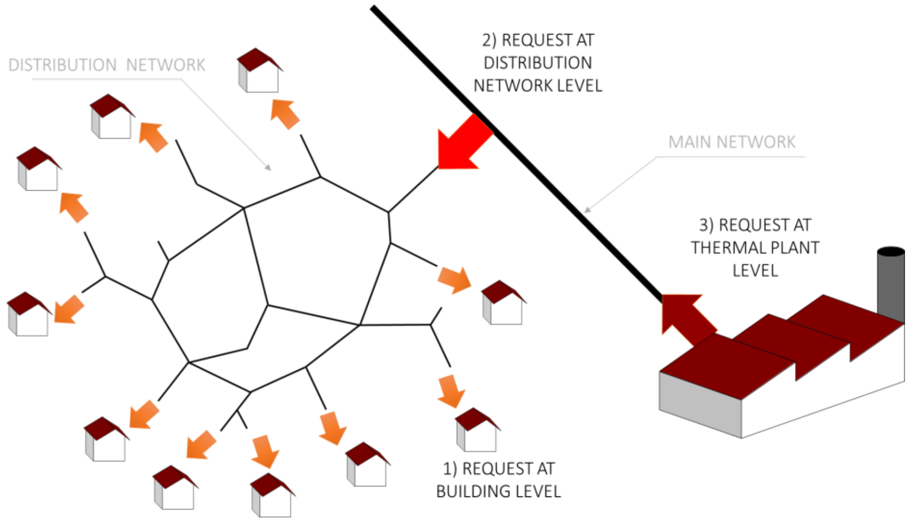

Fig. 6. Request at the various levels

4.1 Request at building level

Fig. 7 shows the results obtained through application of the automatic approach for detecting the main points of the demand profiles. The figure reports the experimental data measured in the substations (in blue) and the points detected using the automatic tool (in black). The points used to represent the curve are:

1. the switching on;
2. the peak;
3. the end-point of the peak;
4. the last time before the system is switched-off;
5. the time the system is switched off.

It is clear from Fig. 7 that the model for the automatic detection of the points perfectly detects all the quantities for all the considered cases.

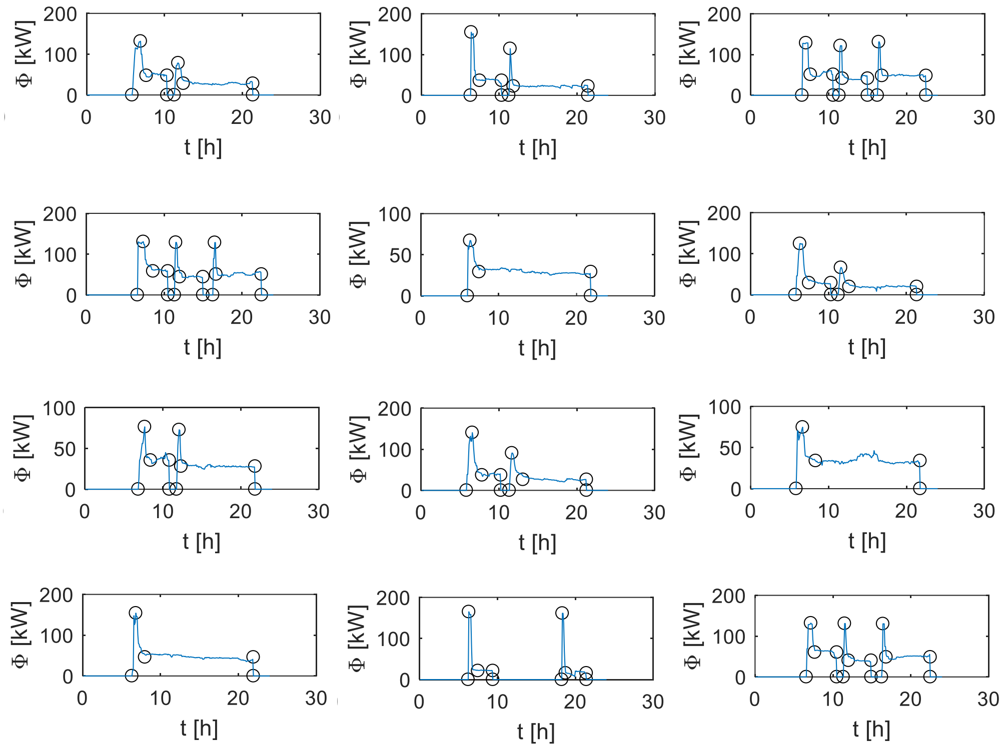

Fig. 7. Results of the tool for the automatic detection of the main curve characteristics

Fig. 8 shows a comparison of the thermal load forecast (dashed red line) and the real evolution (blue line). The thermal demand evolution is well detected in all the cases reported in the figure. The maximum peak values and the steady state conditions are predicted with a good level of accuracy. The peak duration is also well detected. The mean relative error that the model perform is evaluated as the mean error in the evaluation of the main curve characteristics. In particular, the percentage error on the maximum peak is less than 7 %. This is a satisfying result considering i) the very high variability of the thermal request ii) the problems related to the detection of data (one need only think the lack of a data at the maximum peak) iii) the imprecision due to wheatear forecast and iv) the simplicity of the considered model.

As regards the error performed on the prediction of the steady state, this is higher (although less than 15%)) than the ones performed predicting the maximum peak value. This is because especially at the beginning and at the end of the heating season, the steady state value are quite low and the relative error is quite low although the absolute value is small.

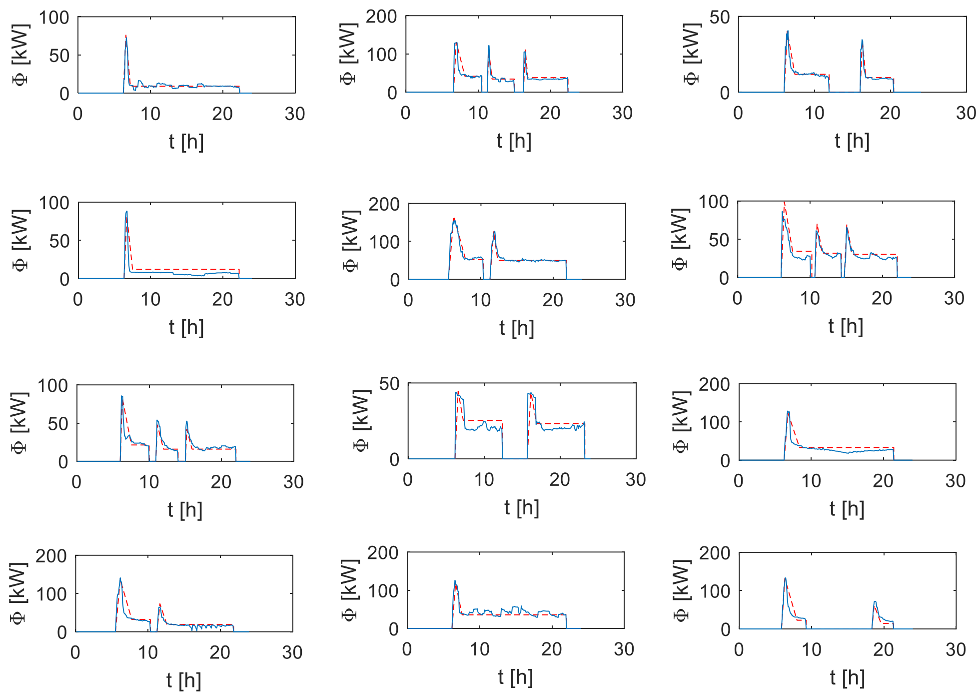

Fig. 8. Forecast model applied to the users of Turin DH system

Another important point is the time that the model takes to provide results, during both the model building and the model use. The tool for the evaluation of the β coefficients (including the pre-processing stages, such as the evaluation of the main curve characteristics) requires low computational times. In particular, in some seconds it allows one to obtain the optimal values of coefficients β for a distribution network. As regards the model use, it only takes about 0.1 seconds. This result is very important because large networks includes various hundreds distribution networks and the model has to be run at least every month in order to include the changes in user request (mainly due to possible rescheduling of the operating hours in the buildings or the implementation of retrofitting measures).

4.2 Request at distribution network level

Fig. 9 shows the total demand at distribution network level, for a typical winter day. Both thermal request and mass flow rate are reported. The errors associated to the prediction of the distribution network request are, on average, lower than the errors at a building level. This is because, when various buildings are considered, the errors at the building level offset each other, because of their different signs.

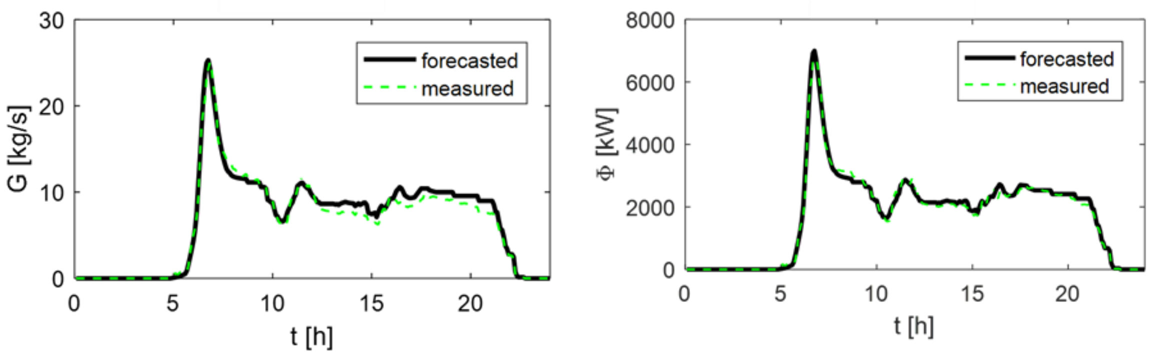

Fig. 9. Mass flow and thermal request and profiles at distribution network level

The effects of the input variation on the error prediction are tested on a complete heating season. This allows taking into account the high variability of cases that can occur. Results are reported in Fig.10 where the relative error for the peak value and the steady state value predictions are shown. The relative error is computed as the difference between the value predicted and the value occurred (experimental data), divided by the maximum value occurred during the year. The errors are weighted respectively on the maximum peak value (in case of peak prediction) and the maximum steady state value (in case of steady state prediction). This allows avoiding mismatches between the error referred to days characterized by different outdoor conditions (characterized by different thermal request). A frequency plot is used to show how frequently a certain error occurs. The figure shows that the error are lower than 5 % in almost all the considered day.

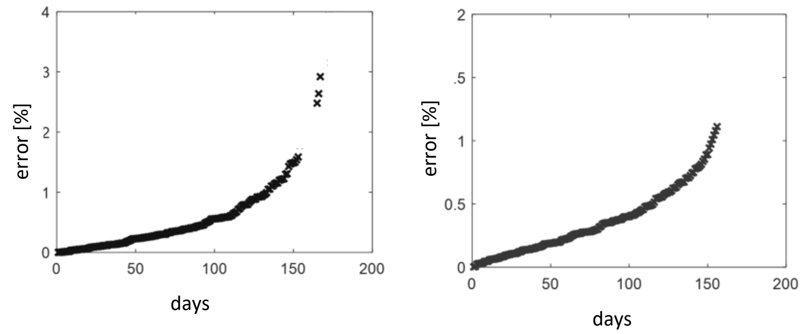

Fig. 10. Errors in the evaluation of the thermal request profile at distribution network level

4.3 Request at thermal plant level

In this section the importance of using a multi-level approach is shown. Fig. 11 reports:

- the thermal demand evolution, evaluated in a thermal plant (black curve);
- the summation of the thermal requests of the buildings connected to the network (in red).

The thermal request is reported between 4 am and 8 am because at this time the thermal peak occurs and the effect of the mixing and the thermal transients. Fig. 11 clearly shows that the thermal request at plant level is significantly different from that at building level. The sum of thermal request at buildings is lower, mainly because of the temperature evolution during transient. At night, the mass of water flow rate in the pipeline is small and the percent thermal losses are high, with a consequent low temperature at night. In the morning, when the heating systems in the building are switched on, a large mass flow rate is processed at the plants and the temperatures in the return line are low. As a consequence, a large peak request occurs. This clearly shows that the multi-level approach allows one taking into account the network dynamics when considering the request in various point (level) of the network.

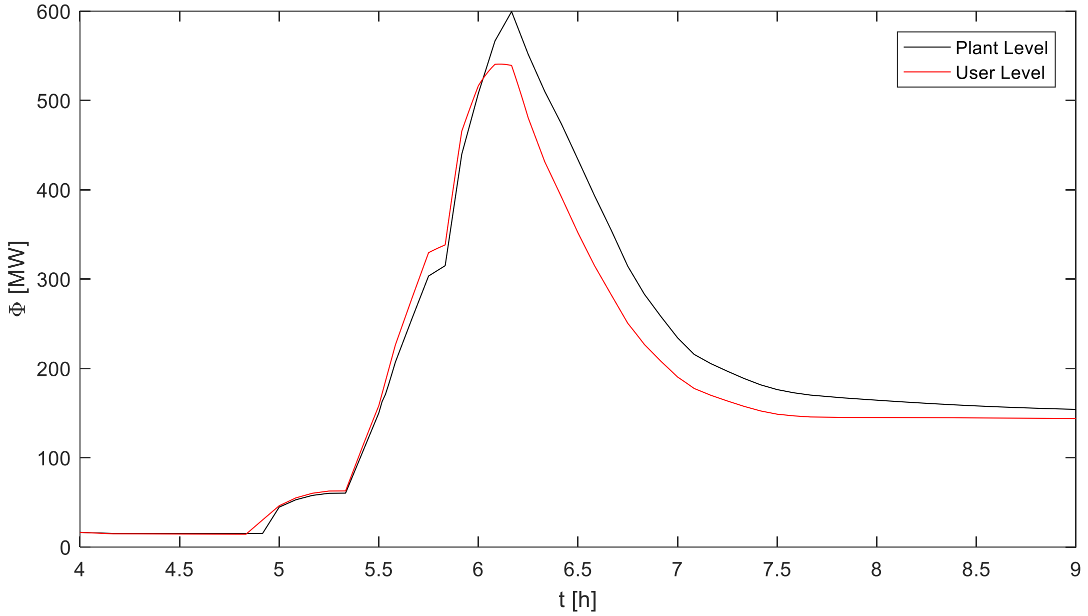

Fig. 11. Comparison of the thermal request at plant level evaluated with and without considering the network dynamics

5. Discussion

A multi-level request predictor is crucial for analysing the management of large DH networks. This is due to the long distances involved, large amount of water and the slow transients. This might make the expected thermal request in a point very different than the actual request. Various analyses rely on the knowledge of the thermal request in various points:

- Demand side management in DH networks requires the knowledge of thermal request at building level. This is because during demand side application:
  - It is necessary to select a certain number of buildings subjected to the modifications of the thermal request;
  - The modification should be properly selected depending on the evolution of the thermal request.
- Thermal requests at building level are required also for exploiting the capacity of buildings as a thermal storage.
- Thermal request in a part of the network should be known when the installation of a thermal storage or a new plant is planned. This is particularly true when the new system is installed with the main aim of overcoming hydraulic bottlenecks while feeding a specific part of the network.
- Installation of heat pumps for increasing the quality of a fluid should be performed once the thermal request evolution in a point of the network is known
- Management of thermal plants depends on the thermal request at plant level. It can be used with the aim of increasing the efficiency or to better exploit the resources from an economic viewpoint. In fact, in case of combined heat and electricity production, electricity production can be more convenient at some hours than others. Modification of the thermal load evolution at plant level may help increasing incomes deriving from electricity selling.

6. Conclusions

In this paper, a multi-level approach to evaluate the thermal request in DH network is presented. The approach used for the predictor of the building request is based on the identification of a series of important curve characteristics for the thermal profile evaluation; these quantities are the peak height, the peak amplitude, the request during steady state conditions. In order to detect the main curve characteristics from historical data, an automatic tool has been carried out. The main inputs influencing the curve characteristics have been evaluated through a correlation analysis. The predictor model of the building thermal request is based on a black box approach. Historical thermal profiles and meteorological data are used for the model construction.
The change of level for the prediction (from building to distribution network and from distribution network to thermal plant) is performed by means of a physical network model. This allows taking into account mixing of water at different temperature, thermal losses and transient.
Results show that the tool for the automatic evaluation of the main curve characteristics perfectly detect the desired quantities. Results also show that the prediction model for both building and distribution network request allows detecting the profiles with a good level of accuracy. The model is suitable for large DH networks, thanks to its compactness (the low number of input parameters and amount of data that have to be managed and the simplicity of application and implementation) ease of use and low computational costs.

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